A diagnostic toolbox for assessing point data generalisation algorithms

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A DIAGNOSTIC TOOLBOX FOR ASSESSING POINT DATA GENERALISATION ALGORITHMS

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1 INTRODUCTION

In recent years, point data have gained in importance in cartography due to new challenges, such as the advent of point-of-interest (POI) data in web and mobile cartography applications, as well as the predominance of point geometries in geographically relevant Web 2.0 services. So far, however, this evolution has not yet been reflected in generalisation research. Compared to line and area generalisa-tion, the generalisation of point features and point sets has received relatively little attention, which have been predominantly studied in large-scale generalisation research projects of the past decade (e.g. AGENT, 1998; Stoter et al., 2009).

Our main interest is in the generalisation of point data for web and mobile applications. Hence, this adds the requirement that suitable generalisation algorithms must have the potential of operating in real-time. Real-time generalisation, however, comes at some cost. In pre-computation, which is the first approach that can be used to achieve real-time behaviour, the cost occurs as loss of flexibility, particularly when multi-scale caching strategies are used. Pre-computation excludes the ability of the system to react at run-time to changes in input data. In the second approach, on-the-fly generalisation, the cost typically occurs as loss of cartographic quality, as real-time solutions must abandon optimisation strategies that lead to superior quality but also to prohibitively high computational effort.

In our work, we rule out strategies that are based solely on caching entire maps at multiple levels of detail (LODs). For pragmatic reasons, such strategies may currently be the ‘industry standard’ for static web maps (e.g. Google Maps), but they are entirely inflexible and cannot accommodate dynamic changes in input data. In the target applications that we have in mind point data, such as POI data, may differ depending on the request made by the user. Thus, we are interested in on-the-fly generalisation algorithms, that is, algorithms that allow the generalised point set to be derived at run-time—and hopefully in real-time—from a more detailed database. Some of the algorithms that qualify for real-time behaviour make use of hierarchical spatial data structures. These data structures may also be stored persistently, and hence can be seen as pre-computation. In contrast to the above caching techniques, which aim to store LODs of entire, ready-made maps, we tolerate such ‘mild’ forms of pre-computation, as they are a direct by-product of real-time generalisation algorithms, and as such could also be by-passed anytime.

The question, then, is how to choose suitable algorithms for real-time generalisation of point data? In previous work (Bereuter and Weibel, 2010), we have proposed a conceptual framework for the generalisation of point data sets, which names several factors that can be used as criteria for selecting suitable algorithms. One of the criteria is certainly the speed of a particular algorithm, necessary to achieve real-time behaviour. While this might seem a particularly ‘measurable’ criterion, it turns out to be rather tricky, as for practical purposes, the speed that can be obtained does depend largely on the particular set-up and the technology that is used. If the generalisation is computed on the server-side, then obviously much more complex computations are possible in a tolerable response time than if generalisation takes place on a mobile client. Thus, we exclude the criterion of computational speed from our considerations here.

In this paper, we are interested in assessing the cartographic quality of real-time algorithms for point generalisation. More specifically, we are interested in tools that can be used to assess cartographic quality. We call these tools ‘diagnostic tools’, and they will form the focus of this paper.

In the remainder of this paper, we will provide an overview of the background and state of the art relevant for this research (§2). We will then introduce the tools that fill our diagnostic toolbox (§3), before demonstrating on several examples how this toolbox may be used to assess the characteristics of point generalisation algorithms (§4). We will end with a concluding section offering a brief discussion and an outlook on future research (§5).

2 BACKGROUND

The background and state of the art of this research involves three topics: Algorithms for real-time point data generalisation; evaluation strategies; and measures and tools for point data.

2.1 Algorithms for real-time point data generalisation

In Bereuter and Weibel (2010) we have reviewed potential algorithms for real-time point data generalisation. As discussed in the Introduction, the actual speed at which a generalisation system can produce an answer to a user request depends largely on the technology and architectural setup used. Nevertheless, we decided to make a first cut by ruling out all algorithms of iterative nature, as their computational complexity and convergence behaviour may quickly become prohibitive. That basically eliminates optimisation techniques and leaves us with relatively straightforward algorithms. It has to be said, though, that for small numbers of point objects optimisation techniques (e.g. for point feature displacement) may well be feasible even today, and even more so in the future.

In the previous paper (Bereuter and Weibel, 2010), we proposed a hierarchical classification of point data generalisation algorithms. On the first level, we distinguished so-called object-directed algorithms that transform the map objects, from space-directed algorithms that transform the map space.

Among the *object-directed algorithms*, we further distinguished point reduction from point displacement algorithms, yielding the following organisation and candidate algorithms:

Point reduction:

• **Selection** (select a subset of points based on attribute): Random selection; select by relevance, Radical Law (Töpfer and Pillewizer, 1966), local priority criteria (Edwardes et al., 2005).

• **Simplification** (select a subset of points based on geometric criteria; e.g. density): Select on proximity tolerance to neighbours ('fuzzy tolerance'); uniform grid; quadtree; e-approximations by squares or rectangles (de Berg et al., 2004).

• **Aggregation** (replace multiple points by placeholder, generating new point locations): Aggregation by hierarchical clustering (Anders, 2003) requires pre-computation; aggregation by hierarchical data structures including k-d trees, quadtrees, R-trees or variants thereof (Burghardt et al., 2004).

Point displacement (move points to new, non-conflicting locations):

Algorithms using an auxiliary grid for overlap detection (Harrie et al., 2004; Mote, 2007); local search (Mackaness and Purves, 2001); greedy snakes algorithm (Kass et al., 1987).

The *space-directed algorithms* deform the map space to make more room for relevant map features, and were subdivided by Bereuter and Weibel (2010) into two sub-classes:

• Focal transformation (deform the map space radially and globally from the map centre): focal projections, e.g. fisheye (Harrie et al., 2002).

• Malleable space (adapt the map space deformation locally to the existing map objects): Laplacian smoothing with dual mesh resampling (Taubin, 2001).

Naturally, combinations and extensions of the above are possible (and we have developed some of these extensions), but we will retain the above selection for the purposes of this paper.

Cartographic generalisation is an inherently subjective process, and hence its evaluation is also ultimately subjective. One possible answer to this problem is to resort exclusively to visual judgment by expert cartographers. However, while expert judgment is certainly valuable and necessary to get the 'full picture', it also implies serious problems in comparing alternative generalisation solutions, as the criteria used by different experts are not clear. Hence, some researchers have proposed strategies to render the evaluation of generalisation solutions more objective and comparable. Stoter et al. (2009) have brought objectivity into their evaluation procedure by using a set of constraints that were defined and assessed by cartographic experts. Bard (2004) proposed and implemented a detailed evaluation procedure that characterises the state of map objects before and after generalisation and compares these states against a set of evaluation functions that define how the generalisation result should look like according to cartographic rules.

2.2 Evaluation strategies

Our objective, however, is different from the above studies. We are not interested in evaluating how well specific cartographic conflicts have been detected and resolved. We are instead interested in knowing how a particular algorithm performs in a more general way, that is, what its characteristics, its strengths and weaknesses are when generalising a set of points across a range of scales. This should allow comparing different algorithms and their behaviour. Ultimately, such information should help choosing the best performing algorithms from the list of the previous section, and also provide hints for potential extensions of existing algorithms. We are, therefore proposing to develop a set of diagnostic tools that allow characterising the behaviour of point data generalisation algorithms quantitatively and visually.

2.3 Measures and tools for point data

For the objective of our study outlined in the previous section, any method is possible that allows to study desirable properties of point data generalisation. We are dealing with point sets, and hence any method from point pattern analysis (O'Sullivan and Unwin, 2003) is potentially useful. A wide variety of measures for point pattern analysis have been developed over the past few decades, and are documented in textbooks such as Ebdon (1985) or O'Sullivan and Unwin (2003). Some measures have been developed more specifically in the cartographic literature, for instance entropy-based measures that express the spatial distribution of points (Li & Huang, 2002; Stigmar and Harrie, in press). Voronoi polygons give an immediate impression of neighbourhoods but also of point density, and have thus been used in several studies (e.g. Li & Huang, 2002). Graph measures can give hints about the internal structure of the point set (Wasserman and Faust, 1994). They are, however, heavily influenced by the use of the Delaunay triangulation of the input points that is used to build the graph. Their value therefore is limited. The Delaunay triangulation can, however, also be used as an auxiliary data structure for other purposes, such as the generation of distance maps between neighbouring points. And, finally, point densities can also be translated into density maps or surfaces by means of kernel density estimation (O'Sullivan and Unwin, 2003).

3 INTRODUCING THE DIAGNOSTIC TOOLBOX

With the aim of assessing the properties of the generalisation algorithms listed in Section 2.1, using the evaluation strategy outlined in Section 2.2, we have developed a toolbox containing diagnostic measures and tools of the types reviewed in Section 2.3. The toolbox was implemented using R, an open source statistics system offering rich libraries for spatial statistics (Bivand et al., 2008), as well as easy ways to implement additional measures and visualisation methods. In the following, we give an overview of some of the main measures and visualisation techniques that have been implemented. They can be distinguished into two broad classes: Global measures and local measures.

Global measures yield a single number that attempts to summarise a particular geometric property for the entire map (Table 1). These measures are particularly helpful when studied in evolution across a range of scales, or in comparison across different generalisation algorithms, or different input data sets with different distribution characteristics (cf. Figure 1). In Table 1, each of the measures is assigned to a category that relates to the geometric property that should be captured by the particular measure. Where the implementation was based on the literature, we give the corresponding reference.

Categories	Measures	References
Global Measures		
Amount of Information	No. of Points, Weighted No. of Points	Stigmar & Harrie (in press)
Centrality	Mean Centre, Median Centre, Modal C.	Ebdon (1985)
Dispersion	Standard Distance	Ebdon (1985)
	Standard Deviational Ellipse	Ebdon (1985)
Proximity	Proximity indicator	Stigmar & Harrie (in press)
	Nearest Neighbour Dist. Distribution	
Spatial distribution	Thematic Entropy	Li & Huan (2002)
	Topological Entropy	Bjørke (1996); Stigmar & Harrie (in press)
	Positional Entropy	Bjørke (1996)
	Geometric Entropy	Bjørke (1996); Li & Huan (2002); Stigmar & Harrie (in press)
	Geometric Ratio	Li & Huan (2002)
	Average Neighbors	Li & Huan (2002)
	Nearest Neighbour Index (NNI)	Ebdon (1985)
Density	Delaunay Triangle Size Distribution	
	Voronoi Cell Size Distribution	
	Local density	Stigmar & Harrie (in press)
Graph Measures	No. of Vertices, Edges	
	Degree	
	Density	
	Transitivity	Wasserman & Faust (1994)
	Diameter	
	Shortest Path	
	Minimum Spanning Tree	

Table 1: *Global measures for characterising point set distributions in the diagnostic toolbox.*

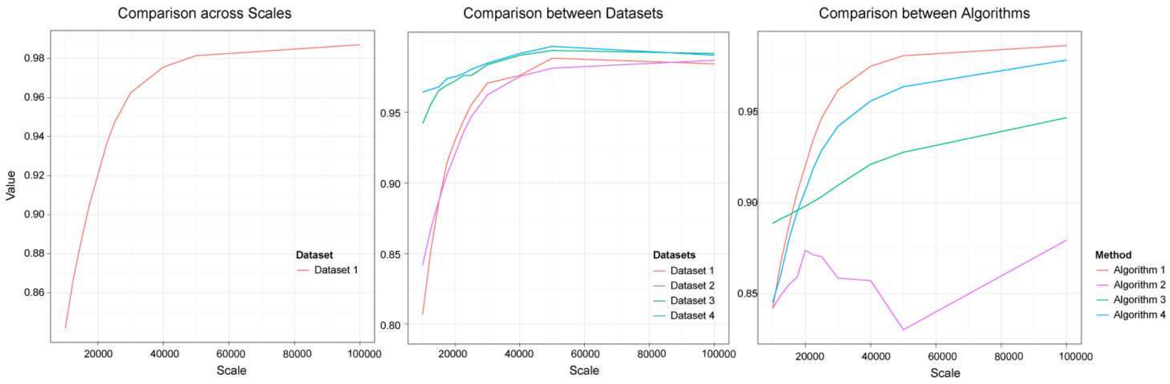

Figure 1: *Strategies of using global measures (on the example of normalised geometric entropy; Li und Huang, 2002).*

Local measures are valid in a local context. They are listed in Table 2, with the same table structure as for the global measures. Kernel density estimation (KDE) yields a field of density values at any location across the map, typically approximated by a raster. In the case of proximity maps, the values represent the distance to the closest point at any location in the map (thus bearing similarity with a raster version of the Voronoi diagram). Both density maps and proximity maps can also be subtracted from each other to generate difference maps and thus identify where change happened between different scales or algorithms. Since local measures can no longer be expressed by a single number, they lend themselves naturally to visualisation, as will be shown in selected examples in the next section.

Besides density and proximity maps, several measures exist in the spatial statistics literature that have been reviewed by Boots and Okabe (2007) and summarised under the heading of 'Local Spatial Statistical Analysis' (LoSSA). These measures can either be computed on the point set or on auxiliary data structures derived thereof, such as the Voronoi diagram. Examples include the local Moran's I and local Geary's C for spatial association, and local clustering measures.

Further measures have been implemented in our prototype system but are not shown in the above tables. Also, additional measures and visualisation techniques would be possible on the basis of those presented here. For instance, geomorphometric statistics could be computed on the density surfaces. Based on experience using the above measures and methods, however, we believe that the above represent a useful set of diagnostic tools to assess the differences and qualities of point data generalisation algorithms.

Categories	**Measures**	**References**
Local Measures		
Density (KDE)	Density Maps	O'Sullivan & Unwin (2003)
	Density Differences between Scales	
	Density Differences between Algorithms	
	Local Voronoi Cell Size Variation	
Proximity	Proximity Maps	
	Proximity Maps Differences btw Scales	
	Proximity Maps Diffs btw Algorithms	
	Nearest Neighbour Link Map	
LoSSA	Local spatial statistical analysis	Boots & Okabe (2007)

Table 2: *Local measures and visualisation methods for characterising point set distributions.*

4 WORKING WITH THE DIAGNOTIC TOOLBOX

Following the summary of tools available in the diagnostic toolbox, we would like to demonstrate how these tools may be used. Besides the elements of the diagnostic toolbox, we also need generalisation algorithms that we wish to test. To date, we have implemented most of the algorithms reviewed in Section 2.1, plus extensions thereof; the remaining ones are currently in the process of implementation.

In order to illustrate the sensitivity of generalisation algorithms to the spatial distribution of the input data, we use four point data sets, as shown in Figures 2 and 3 (left hand column) at the original scale. As the possible combinations of all algorithms against all data sets and measures would be prohibitive given the length of this paper, we restrict ourselves to two generalisation algorithms, both representatives of the typification operator: Mesh filtering (Burghardt and Cecconi, 2007) and quadtree-based generalisation (Burghardt et al., 2004). Figures 2 and 3 show the generalisation of the four input data sets from 1:10,000 to 1:25,000 and 1:50,000. It should be noted that in the examples shown in this paper, we use the mesh filtering algorithm by Burghardt and Cecconi without the density correction factor that prevents points in dense areas from being excessively eliminated. We do that simply for didactic purposes, in order to more vividly show the effects of excessive homogenisation and loss of the characteristic spatial distribution of the input data. With the correction factor on, the results would be clearly better, as shown in Burghardt and Cecconi (2007).

Figure 2: *Mesh filtering algorithm applied to four test data sets (Burghardt and Cecconi, 2007; density correction factor turned off).*

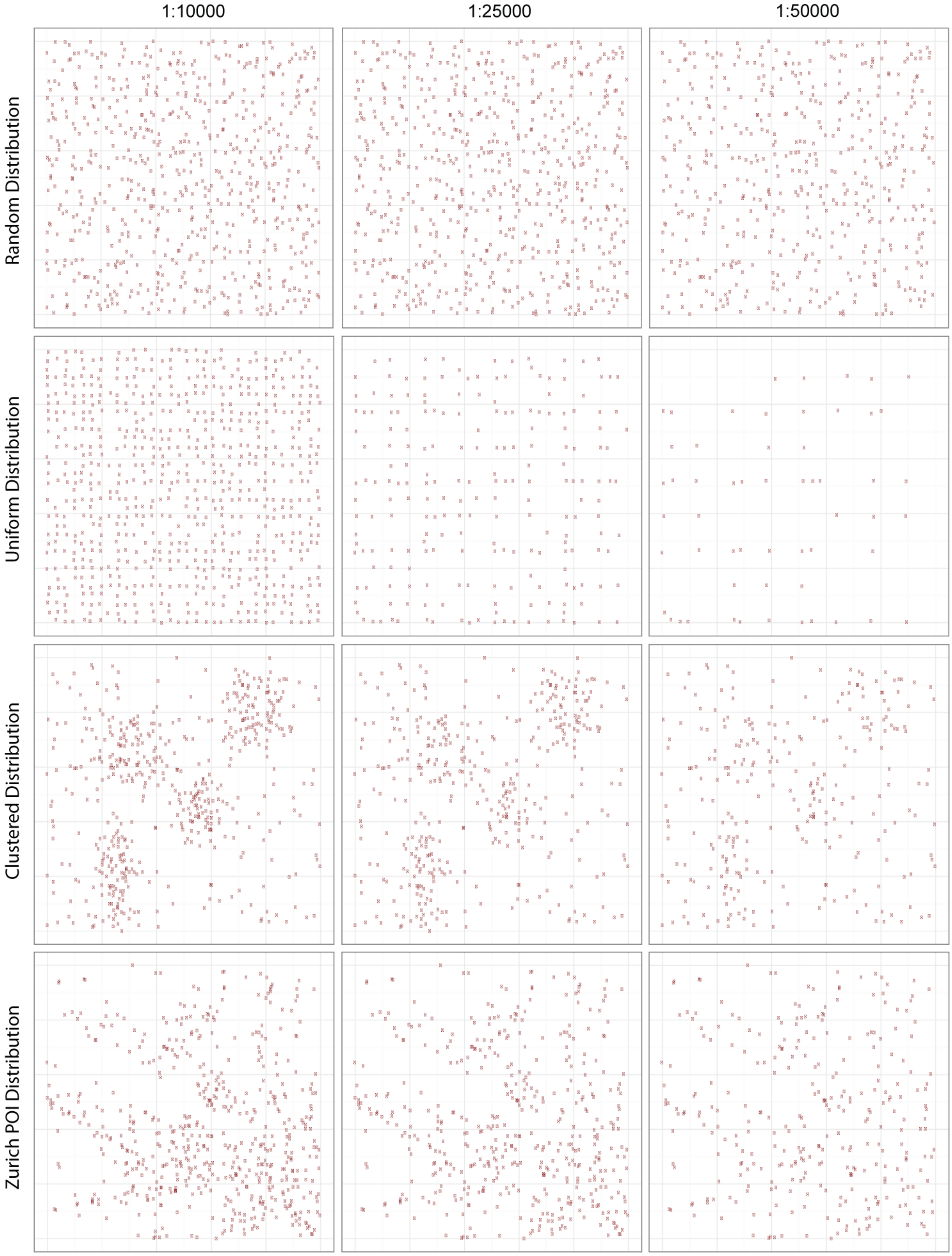

Figure 3: *Quadtree algorithm applied to four test data sets (Burghardt et al., 2004).*

In Figures 2 and 3, it is obvious that the two algorithms have different behaviour in typifying the original point data set. When we apply measures that are capable of capturing the regularity of a spatial distribution, these differences should become noticeable. Figure 4 shows the evolution across a range of scales for the Nearest Neighbour Index R (Ebdon, 1985), computed on the point sets generated by the two generalisation algorithms of the previous figures. The higher the values of R, the more uniform the point distribution that it measures. As the graphs in Figure 4 show, the mesh filtering algorithm approaches the uniform point distribution more rapidly and to a greater degree, independently of the input data set used (once again, however, this effect is mainly due to the density correction factor turned off).

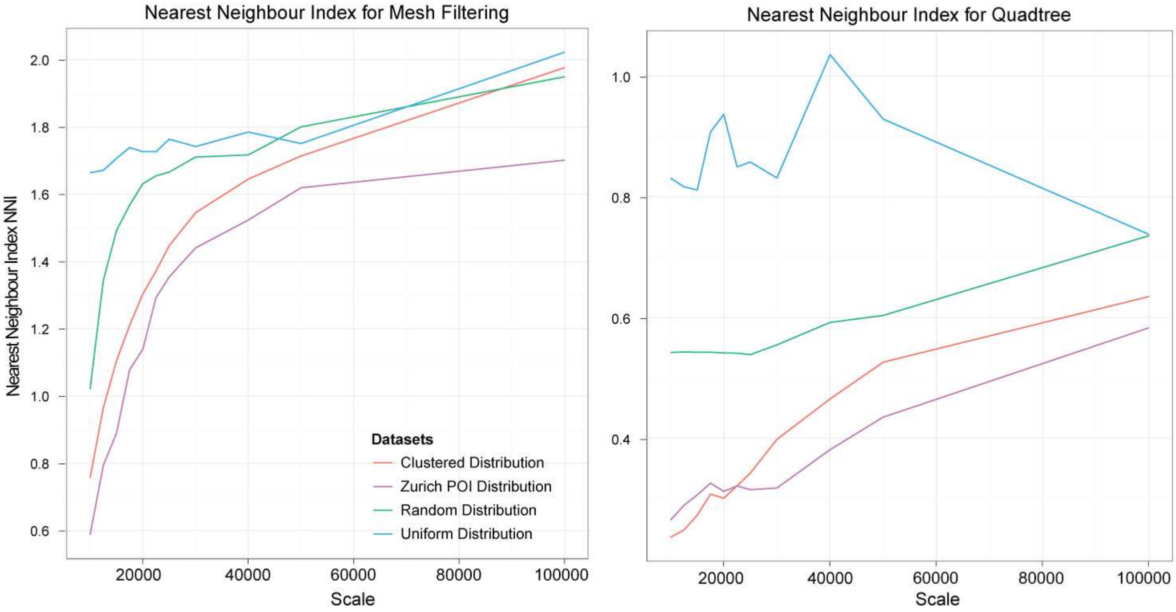

Figure 4: Evolution of the Nearest Neighbour Index for the mesh filtering algorithm (a) and the quadtree algorithm (b).

In the next few figures, we would briefly like to demonstrate how local variations in the results of generalisation algorithms can be quantified and visualised. Figure 5 shows the density surfaces computed by KDE for a portion of the Zurich POI data set at four different scales, generated by the quadtree aggregation algorithm. Visual comparison of the four sub-figures allows assessing where change took place in the scale transitions. However, we can also compute difference maps between the density surfaces and thus get a more immediate impression of the local evolution of point densities over a progression of scales with a single algorithm (Figure 6). Likewise, difference maps can also be computed between the solutions obtained by different generalisation algorithms for a given scale (Figure 7). The example of Figure 8 illustrates the use of a proximity map to render visible the evolution of local proximity relations for a given algorithm and data set. Similarly, our last example, the nearest neighbour link map (Figure 9) shows links between points that are nearest neighbours, and it further depicts half the distance to the nearest neighbours by circles, to give both a qualitative and a quantitative impression of proximity relations.

To conclude this section, it should be noted that while the local measures in the above examples have been solely used for visualisation purposes, they could (and should) equally be used as a basis for further quantitative analysis.

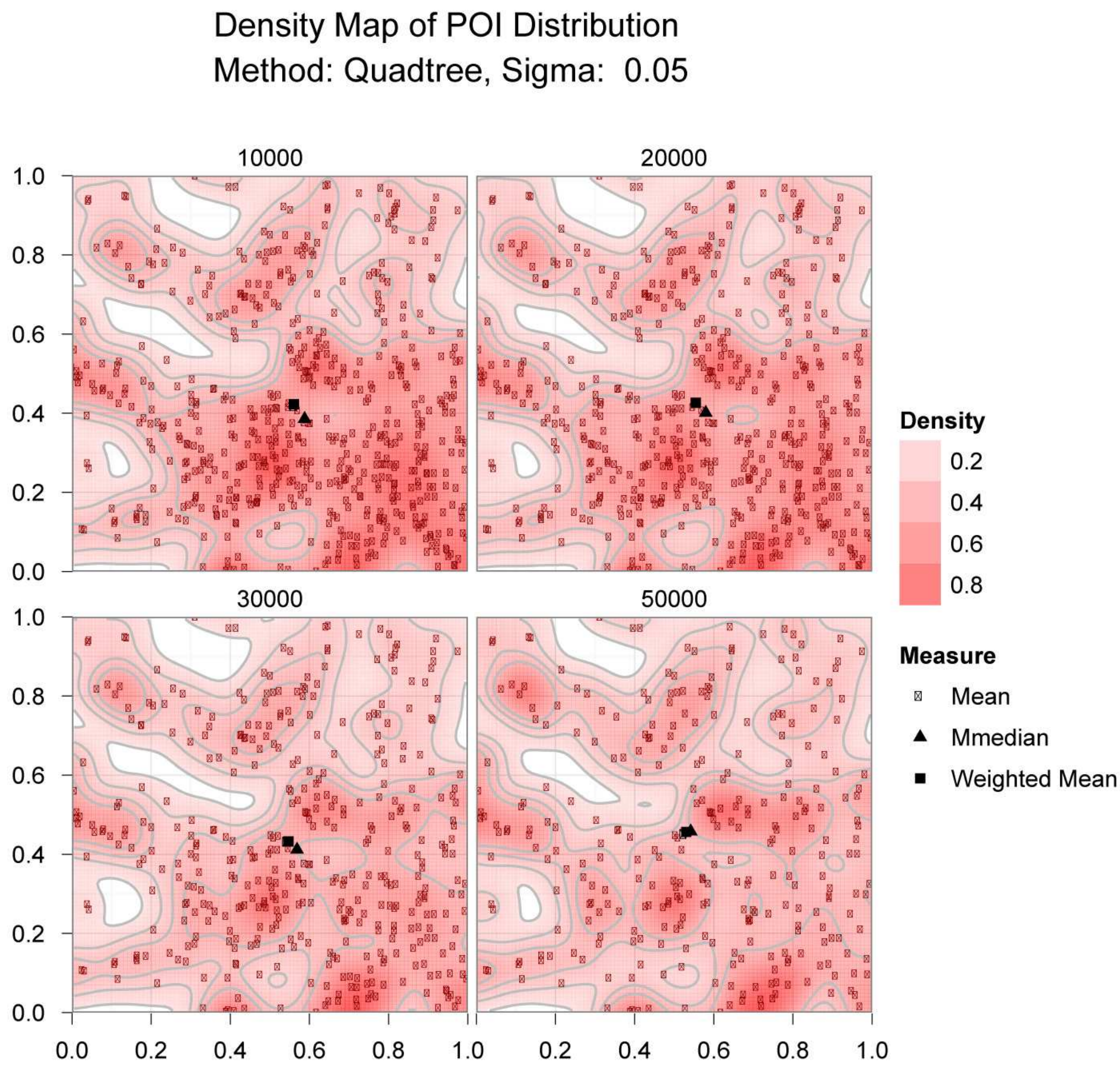

Figure 5: *Density maps (KDE) for four scales of points generated by the quadtree aggregation algorithm (Zurich POI data set).*

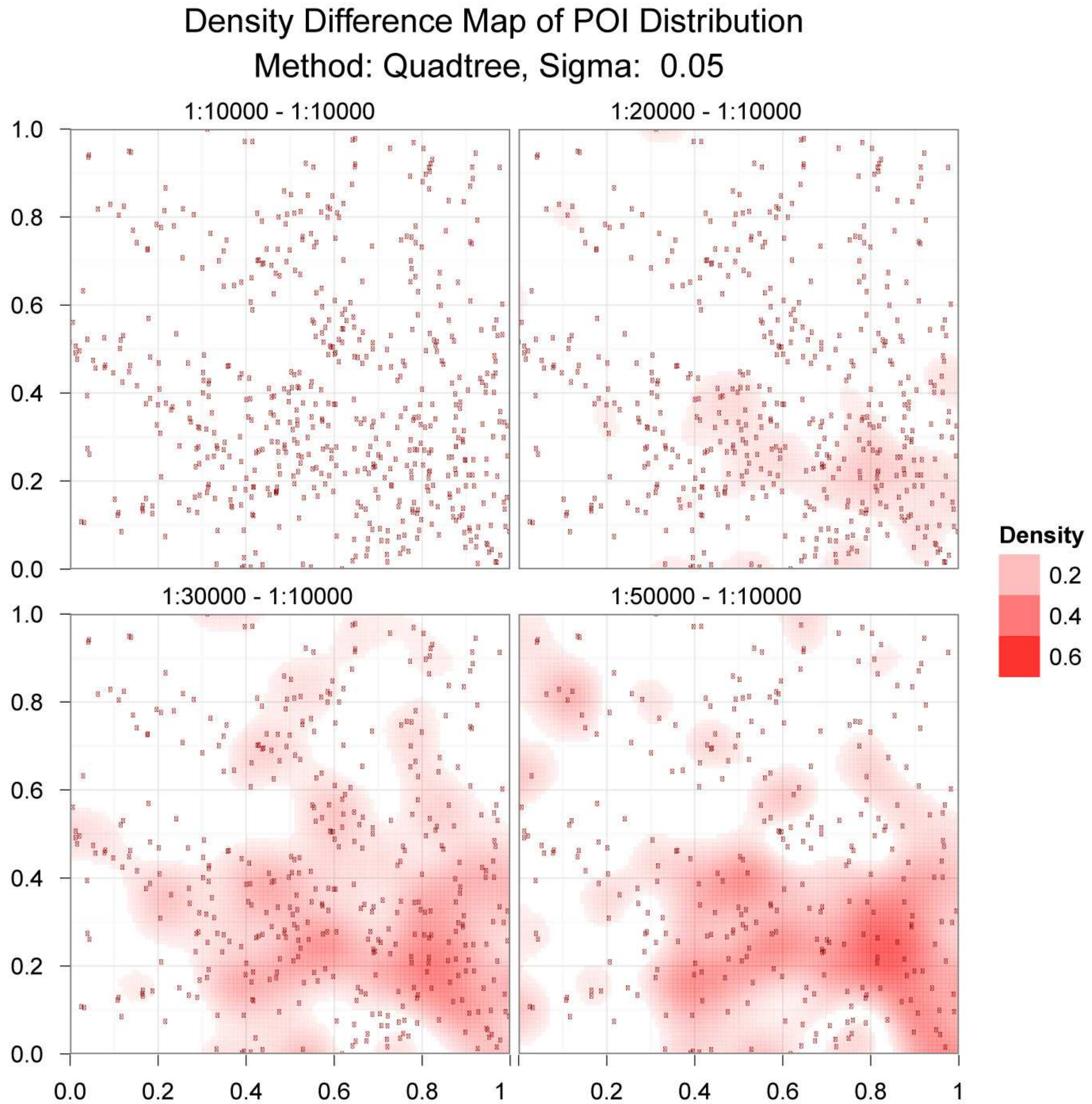

Figure 6: Difference maps between the density surfaces of Figure 5. Differences are always computed from the original.

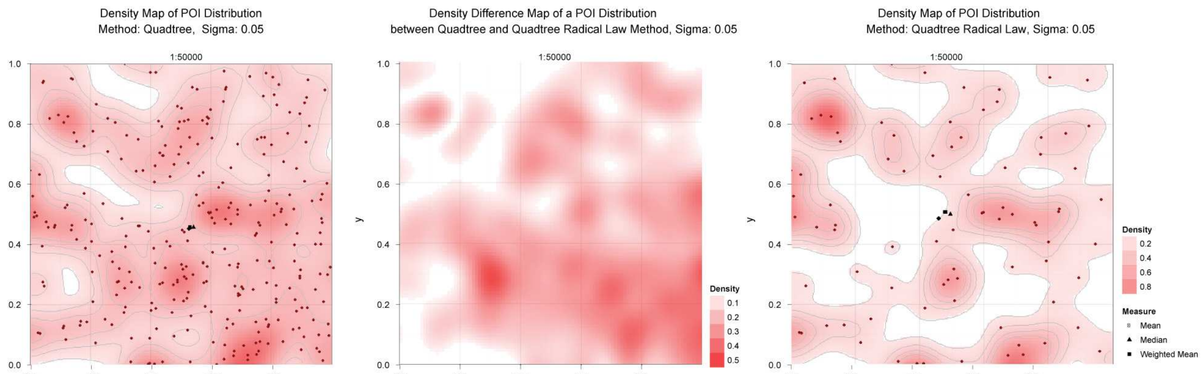

Figure 7: Differences between the results generated by two versions of quadtree aggregation for a given target scale.

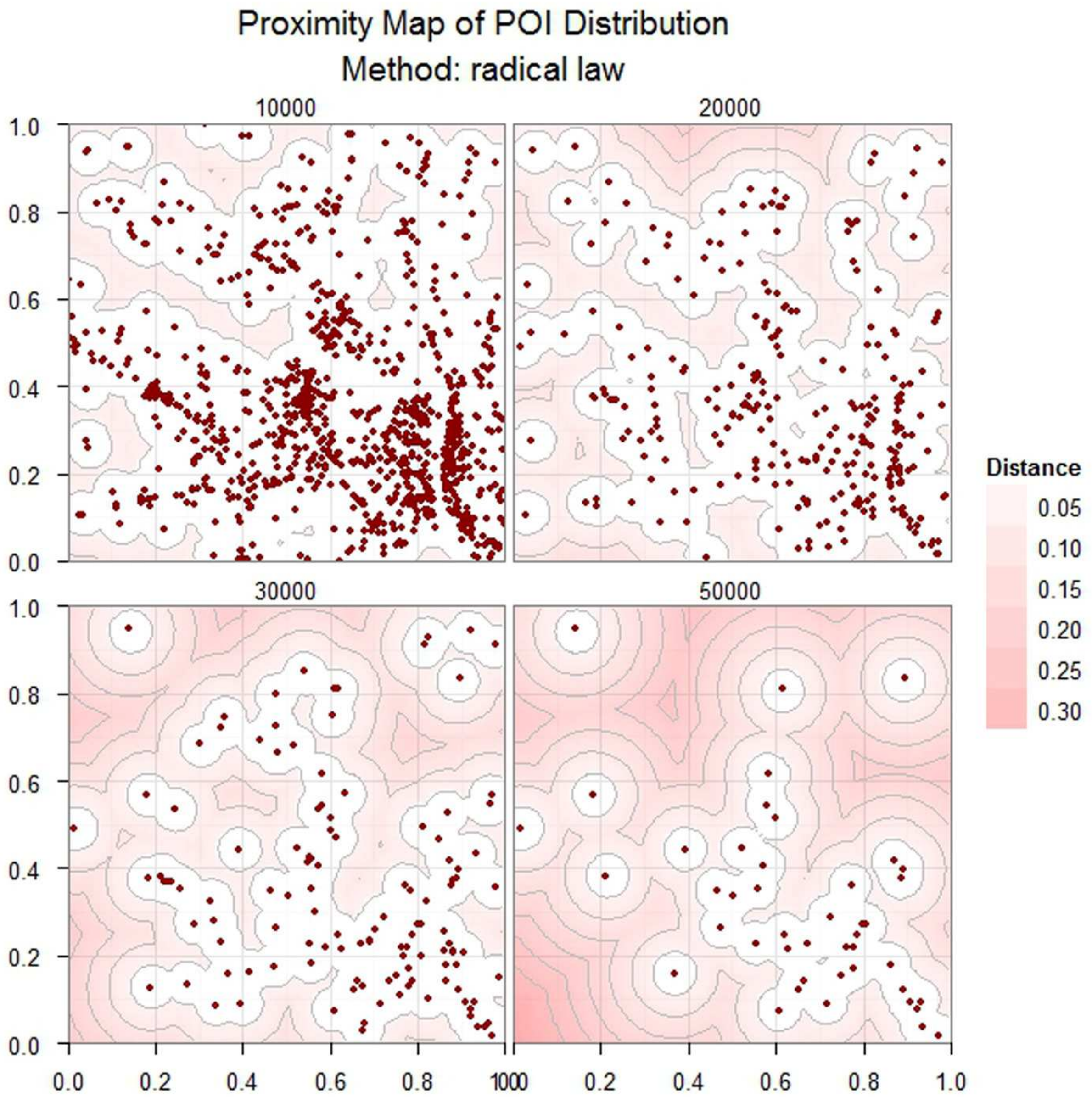

Figure 8: Proximity map for parts of the POI data set. Generalisation method: Random point selection according to number of points determined by the Radical Law.

Figure 9: *Nearest neighbour link map, including Voronoi polygons.*

5 CONCLUSIONS

We have presented a prototype system that offers a set of diagnostic tools that allow to comparatively characterise the behaviour of point generalisation algorithms relative to certain desirable properties, such as maintenance of the distribution and density of the input data. The system was implemented in R. While R is incredibly rich in spatial statistics and spatial analysis techniques (see e.g. Bivand et al., 2008) and allows high productivity in implementing analytical methods, visualisation capabilities are somewhat limited and generating adequate visualisations can be a challenge. However, since data import and export is straightforward, other software packages can be used in conjunction with R to achieve high-quality visual products. Besides the diagnostic toolbox, we have also implemented a range of generalisation methods from the literature (in Java), as well as extensions thereof; further implementations are under way.

We have demonstrated the use of some global and local diagnostic tools in assessing the properties and behaviour of different point data generalisation algorithms. However, we have not yet presented an in-depth comparative analysis of generalisation algorithms. Next steps will involve such detailed quantitative analysis, with the ultimate aim of feeding the results into an automated workflow for point generalisation in web and mobile mapping. Also, we believe that the assessment of generalisation algorithms will provide insight into limitations of those algorithms, which can be used for better algor-ithm parameterisations and generate ideas for alternative approaches.

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